Acta Tropica 190 (2019) 149–156

Contents lists available at ScienceDirect

Acta Tropica

journal homepage: www.elsevier.com/locate/actatropica

Past, present and future of *Aedes aegypti* in its South American southern distribution fringe: What do temperature and population tell us?

Carbajo A.E.[a,b,*], Cardo M.V.[a,b], Vezzani D.[b,c]

[a] Universidad Nacional de San Martín, Instituto de Investigación e Ingeniería Ambiental, Laboratorio de Ecología de Enfermedades Transmitidas por Vectores, General San Martín, Buenos Aires, Argentina
[b] Consejo Nacional de Investigaciones Científicas y Técnicas, Buenos Aires, Argentina
[c] Instituto Multidisciplinario sobre Ecosistemas y Desarrollo Sustentable, Universidad Nacional del Centro de la Provincia de Buenos Aires - CIC, Tandil, Provincia de Buenos Aires, Argentina

ARTICLE INFO

Keywords:
Arbovirus
Argentina
Climate change
Mosquitoes
Vector distribution models

ABSTRACT

Aedes aegypti (Diptera: Culicidae) (Linnaeus) is currently the major threat among arbovirus vectors in the Americas. We examined its past, present, and future distribution patterns in the South American fringe in association with environmental and demographic variables at two spatial scales. We updated the database of the occurrence of *Ae. aegypti* per locality and modelled by GLMM the past occurrence (until 2000) and its expansion (2001–2017) as a function of air temperature, precipitation, altitude, and population. We also conducted a field survey in 7 pairs of urban/rural cemeteries along the entire temperature range within the expansion region. At both scales, mean annual air temperature and human population were significantly associated with the distribution of *Ae. aegypti*. Projection of the expansion models for 2030 under two climatic change scenarios showed a vast infestation, mainly driven by the shift of the 16 °C isotherm. We postulate a quantitative compromise between air temperature and human population associated with vector occurrence, along with potential thresholds for their mutual favourability.

1. Introduction

The container-breeding mosquito *Aedes aegypti* can be currently considered the major threat among arbovirus vectors in the Americas due to its role in the transmission of dengue, Zika and chikungunya (Li et al., 2017), and the possible reintroduction of urban yellow fever (WHO, 2018). In this scenario, the present geographical distribution of the vector and its potential future expansion constitute essential information for disease prevention and control.

Temperature has long been highlighted as a crucial driver of the geographic distribution of *Ae. aegypti* (Bar-Zeev, 1958; Christophers, 1960). During the last decade a bulk of evidence regarding the influence of temperature on *Ae. aegypti* distribution has been published, from local laboratory and field studies to global models (e.g. Brady et al., 2013; Kraemer et al., 2015). The effect of temperature on mosquito development rates is well documented and postulated to exclude other secondary effectors (Couret and Benedict, 2014). At a fine scale, demographic features like human population and urbanization level have also been identified as playing a significant role in the distribution of *Ae. aegypti* (e.g. Carbajo et al., 2006; Tsuda et al., 2006; Rubio et al., 2013). In this context, we previously hypothesized that temperature and demography interact near the South American distribution limit of *Ae. aegypti*, where less suitable temperatures could be compensated by an increase in the urbanization level (Cardo et al., 2014).

Urban environments are heterogeneous mosaics of different land use types, providing a diversity of habitats occupied by arthropods. Among these land uses, cemeteries gather a series of characteristics that make them highly suitable for container-breeding mosquitoes due to the great availability of sugar substances and blood, shelter, and water-filled containers (reviewed by Vezzani, 2007). In particular, cemeteries are widely recognized as strategic sites for monitoring the infestation or reinfestation by dengue vectors (Vezzani, 2007). Also, their relatively homogeneous characteristics make them suitable for comparative purposes. Previous studies within the southern distribution fringe of *Ae. aegypti* in South America explored the relationship between urbanization and vector abundance at different scales, directly by means of the impervious area (Rubio et al., 2011) or indirectly considering vegetation variables (Vezzani et al., 2001). Although the validity of extending

* Corresponding author at: Laboratorio de Ecología de Enfermedades Transmitidas por Vectores, Edificio 3iA, Campus Miguelete, 25 de Mayo y Francia. CP 1650. General San Martín, Argentina.
E-mail address: acarbajo@unsam.edu.ar (A.E. Carbajo).

https://doi.org/10.1016/j.actatropica.2018.11.017
Received 2 August 2018; Received in revised form 30 October 2018; Accepted 15 November 2018
Available online 17 November 2018
0001-706X/ © 2018 Elsevier B.V. All rights reserved.

the results obtained in cemeteries to other land uses is still pending, they might give ancillary information about the relation among temperature, urbanization and the geographical expansion of *Ae. aegypti*. Focusing on a particular land use also allows for the inclusion of variables at a more detailed scale.

Aedes aegypti was considered eradicated from Argentina in the 1960s but reinfestation was confirmed in 1986 in the north of the country. By the year 2000, its distribution had quickly expanded south to Buenos Aires City and its suburbs (reviewed by Vezzani and Carbajo, 2008). After that, a slow but continuous spread to previous free-mosquito areas has been observed, manifested by isolated records to the south in Buenos Aires, La Pampa and Neuquén provinces (Grech et al., 2012; Díaz Nieto et al., 2013; Diez et al., 2014; Zanotti et al., 2015), and to the west in Mendoza, San Juan, and San Luis provinces (MSM, 2009; Visintín et al., 2009; Carrizo Páez et al., 2016). The main competitor *Ae. albopictus* is only present in Misiones Province, over 1000 km north from the southern distribution limit of *Ae. aegypti* (Chuchuy et al., 2018). This offers a unique opportunity to study the variables affecting its geographic distribution without the interference of *Ae. albopictus*.

Assuming that species distribution models are incomplete approximations because the occurrence of any given species is influenced by an unidentified number of interdependent factors that interact spatially in a complex manner (Lobo et al., 2008), we aimed to quantify any potential joint relation of temperature and population on the distribution of *Ae. aegypti*. For this task we (1) related the past and present distribution of *Ae. aegypti* in its South American fringe to selected environmental and demographic variables, (2) examined the association between the relative abundance of *Ae. aegypti* and the environment at a more detailed scale using infestation data from cemeteries, (3) projected vector distribution under future scenarios of climate change and human population growth.

2. Methods

2.1. Study area

Argentina extends from latitudes 22° to 55 °S and encompasses subtropical and temperate regions in northern and southern areas, respectively. The distribution of *Ae. aegypti* has expanded to the west in San Juan (Carrizo Páez et al., 2016), Mendoza (MSM, 2009) and San Luis (Visintín et al., 2009), to the southwest in Neuquén (Grech et al., 2012), and to the south in La Pampa and Buenos Aires (see next section for references). However, negative records are only available for localities within La Pampa and Buenos Aires provinces, and they are a requisite for presence-absence statistical models. Therefore, analyses were limited to these provinces, located at mid temperate latitudes (Fig. 1). Mean annual air temperatures vary from 13.4 to 17.6 °C and cumulative annual precipitation are between 600 and 1000 mm west-east (SADS, 2017). Approximately 40% of the territory is used for farming (corn, soybean, wheat, linen and sorghum) and cattle breeding. Buenos Aires is the most populated province of the country, with 15,625,084 inhabitants (inh) unevenly distributed among dense urban areas and rural zones (INDEC, 2017).

2.2. Distribution database of Ae. aegypti by locality

Geo-referenced information on presence/absence records of *Ae. aegypti* until the year 2000 was compiled by Curto et al. (2002). This database was available at the locality scale, defined as “any spatial concentration of buildings interconnected by a street network” sensu INDEC (2017), and was updated with three information sources: 1- Own record (the first to our knowledge) in the city of Azul, Buenos Aires Province (36°47′S 59°51′W); three fourth-instar larvae were collected by one of the authors (M.V. Cardo) from a cemetery flower vase in March 2017. 2- Published information on scientific journals (Rossi et al., 2006; Vezzani and Carbajo, 2008; Díaz Nieto et al., 2013; Rubio et al., 2013; Diez et al., 2014; Zanotti et al., 2015). 3- Online records by local Health Authorities (accessed in June 2017) (Fig. 2). If *Ae. aegypti* was reported at any locality at least once, it was considered present. All the localities where *Ae. aegypti* was searched for and not found were recorded as absent.

The dataset was restricted to localities south of the 17 °C mean annual isotherm of the period 1995–2000 to exclude Buenos Aires City and its surrounding urban sprawl from the analysis (Fig. 2). In this area, localities are connected in an urban continuum and the population of each district cannot be attributed to a specific location due to vicinity and people flux. Also, this area is assumed infested, whereas the expansion area is under constant search for the vector and new records are reported immediately.

2.3. Past and present Ae. aegypti distribution modelling

2.3.1. Response variable

The occurrence of *Ae. aegypti* per locality was modelled as a function of explanatory variables in two different models. One was for the past distribution, including 97 records of *Ae. aegypti* until 2000 as the response variable, consisting in 25 positive and 72 negative localities. The second was for the expansion of the distribution and was restricted to the area south and west of the limit considered for infestation until 2000. Such limit was defined by joining the southernmost positive records (dark grey solid line in Fig. 2). This subset included 66 of the original 97 localities, 34 negative and 32 positives. Positive localities were 29 records between 2001 and 2017 and the 3 southernmost records until 2000. Localities closer than 5 km between each other were considered as one.

2.3.2. Explanatory variables

We chose to include temperature and human population (as a proxy for urbanization) variables because they are largely documented to determine the geographical distribution of *Ae. aegypti*, they are easily available and they can be projected for future scenarios. Monthly mean air temperature was averaged for 6 years periods based on monthly data from CRU TS3.24.01 (CEDA, 2017). This dataset consists of a 0.5 × 0.5 decimal degrees grid based on local meteorological stations (Harris et al., 2014). Monthly minimum and maximum air temperatures available in the same dataset presented high correlation coefficients (> 0.91) with mean air temperature, and were therefore excluded from further analyses. The two last national demographic censuses were performed in 2001 and 2010 (INDEC, 2017). Population structure in the study area is highly skewed; among the 97 localities, 39 have less than 12,000 in., and only 16 are home to more than 50,000 in.. Among the latter, there are three largely more populated than the rest, with > 250,000 in. (Mar del Plata, La Plata y Bahía Blanca, Fig. 1). To prevent these localities to arise as outliers, besides the continuous population variable (log scale), we also included a factor with three levels, low (< 12,000 in.), mid (12,000–50,000) and high (> 50,000). Two other environmental variables were included in the modelling, because we considered they may significantly interact with temperature and therefore not taking them into consideration would potentially lead us to biased interpretations. These were annual cumulative precipitation (also averaged for 6 years periods and obtained from the same dataset as mean air temperature), and altitude above sea level which was available as isolines (IGN, 2017) and interpolated to a grid of 0.056 decimal degrees pixel size.

2.3.3. Model building

Variables included in each model are shown in Table 1. Continuous variables were first standardized and entered as explanatory variables in a Generalized Linear Mixed Model (GLMM) with binomial error distribution and logit link. Variables retained in the final multivariate models were selected by a stepwise backwards procedure as follows. Different starting models were built including altitude, one variable of

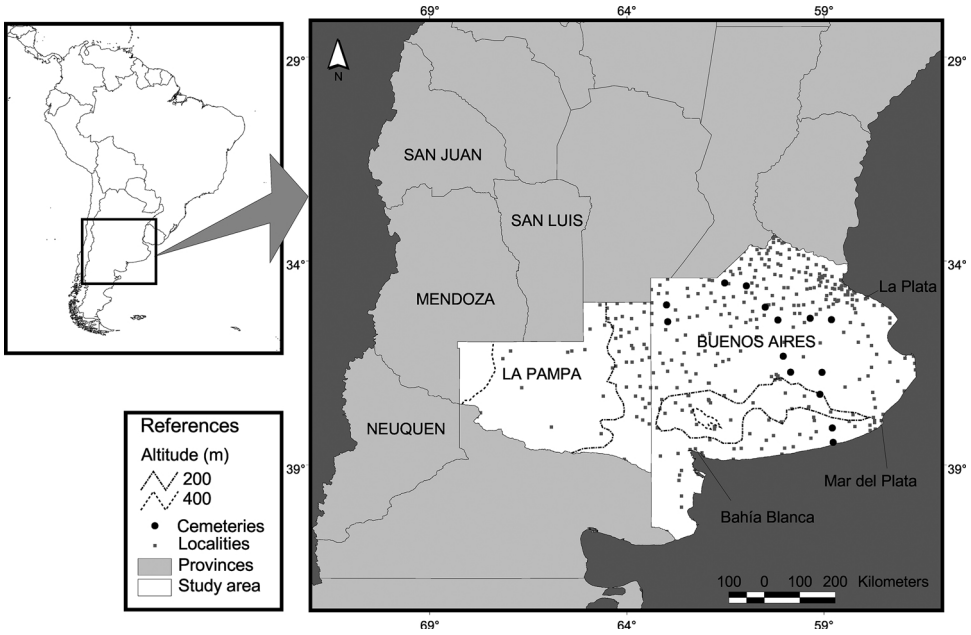

Fig. 1. Study area. Most populated cities in small letter and provinces mentioned in the text in capital letters.

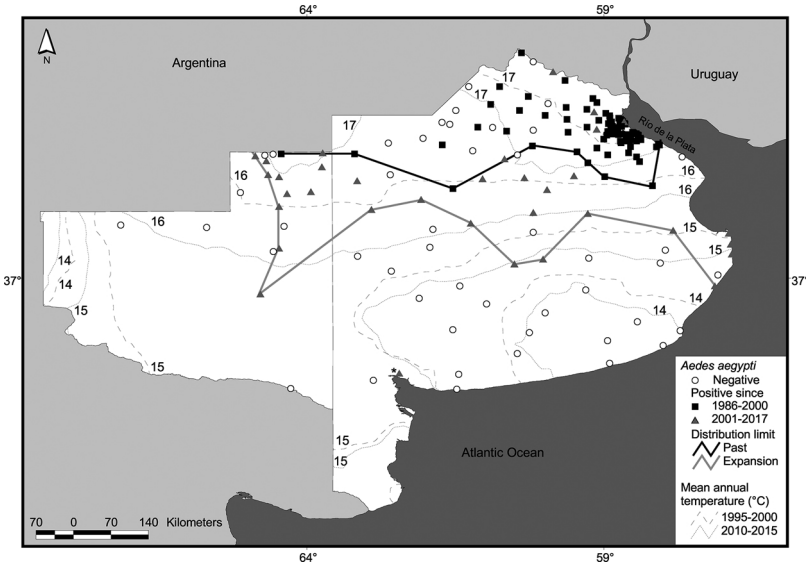

Fig. 2. Occurrence of *Aedes aegypti* within the southern distribution limit in South America until 2000 (past) and 2017 (expansion). The asterisk denotes Bahía Blanca City, excluded in the distribution limit plotting, but nonetheless considered as a positive record in the statistical models.

temperature, one of urbanization and one of precipitation. These could be either the mean for a given period or the change between periods. Quadratic relations and two-way interactions were also added if they did not incur in colinearity issues (variance inflation factors < 5, Zuur et al., 2009). Given that the number of positive and negative localities was unbalanced between provinces (24 positive and 56 negative in Buenos Aires, 1 and 16 in La Pampa), we included the province as a random factor. The levels in the categorical population variable that were not significant were merged together. The selected model for each response variable (past distribution and expansion) was the one that yielded the lowest Akaike information criterion (AIC) value. Model parameters were refitted after data bootstrapping (1000 replicates) to discard the effect of very influential observations. To evaluate model assumptions and goodness of fit, graphical verification was performed by examining the residuals versus fitted, residuals versus Leverage and normal Q-Q plots.

To assess the accuracy of the selected models, the Cohen´s agreement Kappa index (K), which indicates the classification improvement of the final model over chance, was calculated. Given that the predicted values are a probability between 0 and 1, the occurrence of *Ae. aegypti* was initially considered at a threshold probability of 0.5 for all models. Then, an optimisation procedure selected an alternative cut-off point (labelled acp, after 'adjusted cut-off point') that maximized the classification effectiveness of the model as follows. The value of K was calculated for each 0.01 cut-off point between 0 and 1, and the point that provided the best value of K was chosen. We reported the mean K value of ten rounds of 10-fold cross-validations along with its corresponding standard deviation, both for the original and optimized cut-off points. Modelling was performed using the open-source software R 3.2.3 (R Core Team, 2016), with lme4, car and boot packages for the inclusion of the random component, vif testing and data bootstrapping, respectively. Spatial data processing was performed with QGIS 2.10.1 Pisa.

After model building, the GLMM for the expansion of the

Table 1
Environmental and demographic variables used for modelling past, expansion and future distribution of *Aedes aegypti* in its American southern fringe.

Aedes aegypti records	Past	Expansion	Future
Climatic annual average period	1986-2000	2001- 2017	2025-2030
	1995-2000	2010-2015	2025-2030
Mean annual temperature (ºC)	T95_00	T10_15	T25_30&
Cumulative annual precipitation (mm)	Pp95_00	Pp10_15	
Population# **(log** inhabitants)	Lpo01	Lpo10	Lpo25
Population# categories (low, mid, high)+	Pcat01	Pcat10	Pcat25
Temperature difference (ºC) T10_15 - T95_00		Dite10-15	
Precipitation difference (mm) Pp10_15 - Pp95_00		Dipp10-15	
Temperature relative difference (–) (T10_15-T95_00) / T95_00		Dire10-15	
Log population difference **(log** inhabitants) Lpo2010 - Lpo2001		Dipo10-01	
Population relative growth (–) (po2010 - po2001) / po2001		Pogw10-01	
Altitude above sea level (m)	Alt	Alt	

#Data correspond to the population according to 2001 and 2010 censuses and the projection for 2025.
+Cut-off points for the categories were 12,000 and 50,000 in.abitants.
&Two temperature variables were used based on RCP 4.5 and RCP 8.5.

distribution (n = 66) was used to predict the occurrence of *Ae. aegypti* in all localities of the study area that met the following inclusion criteria: mean annual air temperature < 17 °C as explained above and population > 400 in., given that no locality below that number was present in the training set. The resulting number of predicted localities was 408.

2.4. Ae. aegypti in cemeteries

2.4.1. Field survey

To obtain ancillary information about the occurrence of *Ae. aegypti* in relation to the environment at a more detailed scale, a field survey in cemeteries was performed. Out of a subset of 80 public cemeteries within the study area, we selected 14 within the expansion zone of *Ae. aegypti* and further south, including the entire mean annual air temperature range in the region (Fig. 1). To consider the urbanization level around cemeteries, sampling design was arranged in 7 urban/rural cemetery pairs from North to South as follow: Junín/Vedia, América/General Villegas, Bragado/Veinticinco de Mayo, Monte/Roque Pérez, Azul/Tapalqué, Tandil/Rauch, and Necochea/Lobería (Fig. 1). Each cemetery was inspected for immatures of *Ae. aegypti* in water-filled flower vases by active search (same three operators during 1 h) during March 2017. This month was selected because previous studies recorded the highest abundance of the mosquito as immatures in artificial containers (Rubio et al., 2011).

2.4.2. Model building

The infestation levels of *Ae. aegypti* varied greatly among cemeteries, from absence (0 records out of 90 inspected containers) to over 40% of the containers (36/85) harbouring immatures. To analyse this, the Container Index (CI) was defined as the number of positive containers relative to the total number of containers with water inspected per cemetery, and considered an estimator of relative abundance (Silver, 2008). The CI was modelled in a quasibinomial proportion GLM (to account for overdispersion in the data), including as explanatory variables the same temperature, precipitation and urbanization variables described for localities plus certain intrinsic characteristics of cemeteries which have been previously speculated to affect the abundance of *Ae. aegypti* (Vezzani, 2007). These were total and shaded area (in m^2, calculated using Google Earth images and spatial processing in GIS-Arcview 9), and ground cover (cement/grass, recorded in situ). Taking into account the typical dispersion range of *Ae. aegypti* (100 m) and the maximum reported (800 m) (Honorio et al., 2003), we also included the human population in a radius of 200 and 1000 m around each cemetery, obtained by spatial processing of population data at radius tract scale from INDEC (2017). Finally, to account for potential infestation sources we included the linear distance to the centre of the nearest urbanization and open-air garbage dump (both in km and calculated from Google Earth images).

2.5. Future projection

To forecast future potential distribution, the models obtained for the expansion of the distribution (period 2001–2017) were projected maintaining the same parameters and updating climatic and demographic variables. We chose the period 2025–2030 because demographic national data was only forecasted until 2025. Population predictions were available at the district level (INDEC, 2017), therefore we assigned a fraction of such population to each locality within a given district by applying the same proportion of population of the locality respect to the district total in 2010.

Air temperature and precipitation data for future years were obtained from the 3rd National Communication on Climate Change (SADS, 2017). This report studied the error of several global and regional models to predict CRU present data (CEDA, 2017) in order to model future scenarios. The Community Climate System Model (CCSM4) performed among the four best models for central and humid Argentina, where our study area is located. We used the scenarios built with the CCSM4 according to the Representative Concentration Pathways (RCPs) 4.5 and 8.5 (SADS, 2017). These two RCPs are different hypothetical scenarios of greenhouse gas concentration trajectories until 2100, the former is a moderate scenario with emissions peaking in 2040 and then declining and the latter assumes a continuous growth in emissions (Meinshausen et al., 2011).

3. Results

3.1. Past and present distribution of Ae. aegypti

3.1.1. Localities

For past mosquito distribution, i.e. up to the year 2000, two equivalent multivariate models in terms of accurate classification were obtained (Table 2). Both included the mean annual air temperature during 1995–2000 along with a demographic variable: population number in 2001 in model 1 and population number in 2001 arranged in two categories (pcat low < 12,000 in., mid_high ≥ 12,000) in model 2. Cumulative annual precipitation, altitude and all two-way interactions, were not retained among the best predictors. For both models, the Kappa index was high, and 88 out of the 97 localities were correctly classified. The inclusion of the province as a random factor resulted in no significant improvement in either model.

Regarding the expansion of the mosquito distribution, i.e. period 2001–2017, the two best models included the same variables as those of the past distribution. These were the mean annual air temperature

Table 2
Selected multivariate models for the occurrence of *Ae. aegypti* until the year 2000 (models 1 and 2) and for the expansion between 2001 and 2017 (models 3 and 4) using localities data. K is for the Cohen´s Kappa agreement index, SD for standard deviation, acp is for adjusted cut-off point. Miss-classification percentages, false positives and negatives were calculated considering acp.

	Parameters	K(0.5) ± SD(0.5)	acp	K(acp) ± SD(acp)	Miss-classification (%)	False positives/ false negative
Model 1	−3.20 + 1.63 x T95_00 + 4.02 x lnpo01	0.69 ± 0.03	0.42	0.75 ± 0.03	9.3	4/5
Model 2	pcat_low: -5.21 + 4.22 x T95_00 pcat_mid_high: -1.97 + 4.22 x T95_00	0.70 ± 0.02	0.39	0.76 ± 0.03	9.3	5/4
Model 3	−0.09 + 2.68 x T10_15 + 1.97 x lnpo10	0.67 ± 0.02	0.29	0.76 ± 0.02	12.1	7/1
Model 4	pcat_low: -3.22 + 3.53 x T10_15 pcat_mid_high: 2.69 + 3.53 x T10_15	0.76 ± 0.02	0.46	0.76 ± 0.03	12.1	6/2

during 2010–2015 along with a demographic variable: population number in 2010 in model 3 and population number in 2010 arranged in two categories in model 4 (Table 2). Contrary to the expected, changes in temperature or in precipitation between periods were not retained in the best models. Once again, the inclusion of the province as a random factor did not improve the models. Although classification accuracy of both models was equal, when applying the parameters to all the localities within the study area model 3 performed better in capturing the population gradient at high temperatures. As population was considered in two categories in model 4, at northern latitudes the effect of temperature ruled out the population gradient, and all localities were classified as positive.

It is worth noting that no positive records for *Ae. aegypti* have been reported in localities with mean annual air temperature below 14.5 °C. In the range 14.5–15.5 °C, only localities with more than 22,000 in. are infested, whereas in the interval 15.5–16.5 °C, localities with more than 8000 in. are positive (Fig. 3). As temperature increases, the population threshold decreases; above 16.5 °C, the minimum number of inh in positive localities is only 1100.

3.1.2. Cemeteries

No immatures of *Ae. aegypti* were collected in the five southernmost cemeteries. Northwards, the Container Index varied between urban (mean CI = 0.24 [min 0.02; max 0.42]) and rural (mean CI = 0.05 [min 0; max 0.17]) cemeteries. The best model for the relative abundance of *Ae. aegypti* within cemeteries was also a function of climatic and demographic variables. These were the mean annual air temperature in 2010–2015 (T10_15) and the population density in a radius of 200 m around the cemetery border, both positively associated with the response variable (parameters 1.32 and 0.57, respectively), which explained 70.6% of the total variability. Intrinsic cemetery features and distances to the centre of the nearest urbanization and open-air garbage dump added no significant explanation. The localities model 3 correctly predicted the occurrence of *Ae. aegypti* in all the inspected cemeteries, whereas model 4 misclassified only one.

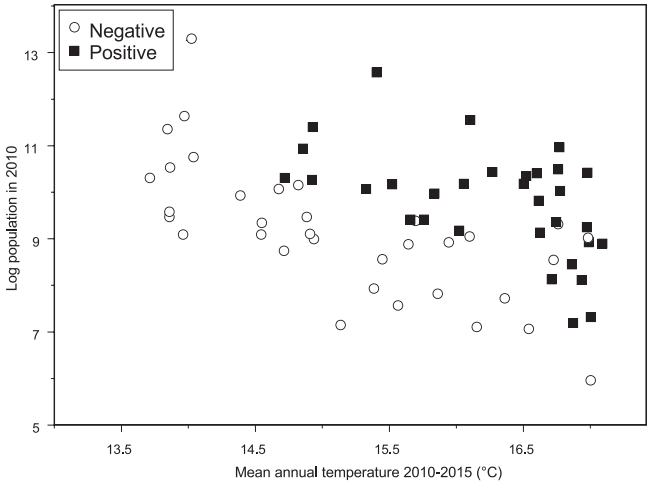

Fig. 3. Human population number in 2010 (log scale) as a function of mean annual temperature during the period 2010–2015 in each locality according to the occurrence of *Aedes aegypti*.

3.2. Future projection

Using the output of the localities models 3 and 4 for the expansion of the distribution and considering two climate scenarios resulted in four projections for the future geographic distribution of *Ae. aegypti* in its South American distribution limit. To fulfil the requirements of the original models, localities with mean annual air temperatures > 17 °C in 2010-15 were excluded, as no data in this temperature range was used in training the models and assuming that *Ae. aegypti* will be readily distributed along this region in the future. Likewise, localities with predicted population < 400 in. in 2025 were not considered. Within the resulting subset (n = 295), 177 localities will be positive for *Ae. aegypti* according to the four models and 61 under none. New positive localities are predicted to cluster in the East of La Pampa and West of Buenos Aires provinces. The distribution of the vector is expected to expand to the south, driven mainly by the shift of the 16 °C isotherm. Below 16 °C positive and negative localities alternate (Fig. 4). The model with continuous population shows more localities with presence according to both climatic scenarios in the south of Buenos Aires Province (Fig. 4a), while the two population categories model covers almost all the north of La Pampa and Buenos Aires provinces with presence according to both climatic scenarios (Fig. 4b). In the two alternative models, differences in predictions by both scenarios lay between 16 and 17 °C.

According to the two climate scenarios considered, mean annual air temperature in the entire study area is expected to exceed 15 °C, which is suitable for *Ae. aegypti* proliferation. Once again, models describe vector presence as a compromise between population and temperature, by which less populated localities require higher temperature for mosquito presence. In the opposite sense, localities with low temperatures could become positive as human population size increases. The minimum temperature-population relation derived from model 3 is a linear function with intercept 36.1 and slope –1.74 (Fig. 5). Therefore, to be infested localities below 14 °C would need more than 121,000 in. and localities below 400 in., temperature values above 17.3 °C.

4. Discussion

Mean annual air temperature and human population were significantly associated with the past occurrence of *Ae. aegypti* (i.e. 1986–2000) and its expansion (2001–2017) in the fringe of its distribution in South America taking the locality as spatial unit, and with the abundance of the vector at the cemetery scale. Based on these results, we postulated a quantitative compromise between temperature and human population associated with vector occurrence, along with potential thresholds for their mutual favourability. Our results suggest

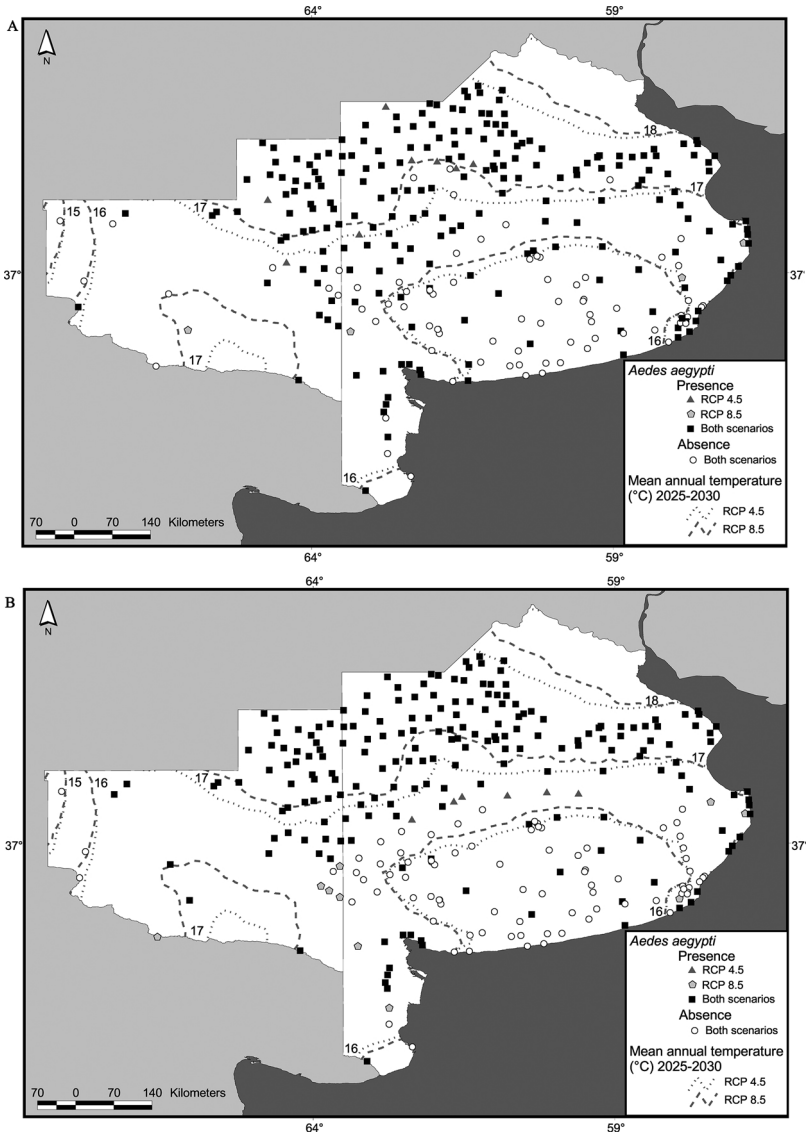

Fig. 4. Projected geographic distribution of *Aedes aegypti* for 2025–2030 in its South American southern fringe. a) Continuous population model b) Two population categories model. Dots show forecasted mosquito presence or absence according to one, both or none of the temperature scenarios.

there is an inhabitants' minimum threshold for localities to harbour *Ae. aegypti* depending on the mean temperature, both variables compensating one another. This process would operate within a limited range, because low temperatures are expected to limit the mosquito establishment above certain latitudes (Brady et al., 2013). An urban heat island effect (i.e. the phenomenon in which a city is warmer than its adjacent rural area) has been described in Buenos Aires metropolitan area (Camilioni and Barrucand, 2012). Although the biggest cities considered in the present study are twenty times smaller, a compensation of low temperatures by an urban heat island effect cannot be discarded. Alternatively, bigger localities may offer a wider diversity of environments, some of which may allow mosquito survival closely below the restricting temperatures.

Regarding the mechanism by which *Ae. aegypti* expands its distribution, more densely populated areas could be infested faster and earlier, because they are more prone to receive containers with eggs through commerce or movement by citizens (Gubler, 2011). In North America, cemeteries have been described as a means of colonization of new territory by *Aedes* mosquitoes, due to the transfer of floral baskets among them and a further spread from the local cemetery to the neighbouring locality (O´Meara et al., 1992). In Argentina, however, there is no such practice and flower vases are rarely carried from one cemetery to another. About half of the containers used as flower vases in cemeteries are introduced by visitors from their homes despite of the prohibition by local authorities (Vezzani, 2007). Therefore, early infestation of a city followed by colonization of the cemetery is a more plausible pattern. Besides passive invasion through introduced containers with eggs, this colonization could be mediated also by active dispersion from nearby premises or rubbish dumps.

Within a vector distribution model, false negatives are generally more relevant than false positives. The latter are questionable, given that a species present in very low abundances may not have been recorded, or could be interpreted as localities in which conditions for vector proliferation are given but not enough invasion pressure has yet occurred. Mar del Plata is a particular case because it is the greatest tourist centre and the most populated city of the study area (614,350 in. in 2010). Mean annual air temperature, however, is slightly above 14 °C and maybe *Ae. aegypti* could be established in the near future (as predicted by one of the expansion models) or even currently present but not detected or documented. On the contrary, false negatives represent a truly misclassified point, even though a single or few records of immatures and/or adults does not guarantee an established population of

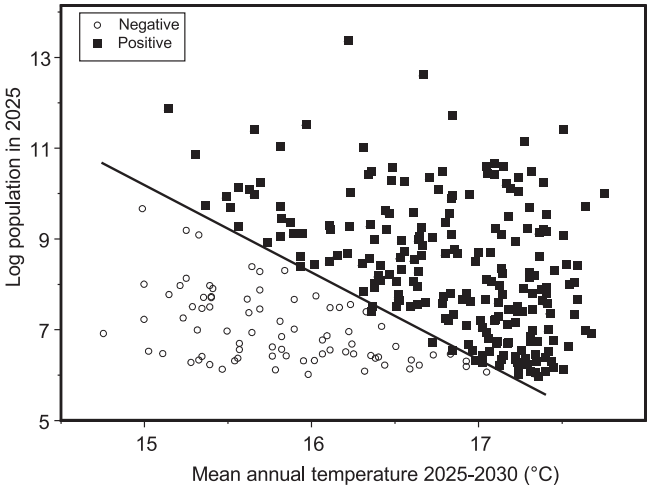

Fig. 5. Human population number in 2025 (log scale) as a function of mean annual temperature during the period 2025–2030 according to the projected occurrence of *Aedes aegypti* with generalized linear model 3. The solid line indicates the lower temperature and population boundary for *Ae. aegypti* presence. The x axis shows temperature under scenario RCP 4.5; correlation coefficient with RCP 8.5 = 0.988.

RCP 4.5; correlation coefficient with RCP 8.5 = 0.988.

Ae. aegypti. Villa Gesell was incorrectly classified as negative in both expansion models. This tourist city has a year-round population of 31,730 in. but is prepared to receive approximately ten times more during the summer. In other words, in tourist areas, as the urbanization level is much higher than that suggested by the census population, the latter may not be a good proxy for the urbanization level.

Regarding future projections, we expected temperatures based on the RCP 8.5 scenario to be slightly warmer than those of the RCP 4.5. In Fig. 4, some areas of reverse relation were found, although the results of the models for both scenarios are quite similar. Nonetheless, main differences between these scenarios are expected after 2050 (Meinshausen et al., 2011). The modelled distribution of *Ae. aegypti* for 2025–2030 showed a vast infestation in the north of the study area under both scenarios. As except for West La Pampa most of the study area is expected to reach air temperatures above 15 °C, human population would ultimately be the main limiting factor in the region. Notwithstanding this, potentially unpredictable changes in urban and suburban environments may significantly influence the relation between human population density and *Ae. aegypti* occurrence, because of urban heat islands, microclimatic changes in humidity or changes in water storage practices, among other factors. The exercise of forecasting future distributions does not intend to predict exactly where colonization will occur but to depict general trends, identify processes, and assess models behaviour.

In brief, air temperature and human population were identified as key variables representing climatic and demographic characteristics that only jointly describe the occurrence of the dengue vector near its distribution limit in South America. In contrast with global distribution models, our research contributes with a detailed scale analysis and this approach could be adapted to local scenarios in other fringes of the geographic distribution of *Ae. aegypti* worldwide. Within the context of global climatic and demographic change, the expansion of the *Aedes* mosquitoes into current free areas could be expected, with the unavoidable risk of spread of the diseases they transmit.

Acknowledgements

We are thankful to CIMA/CONICET-UBA for the provision of climatic data of the 3rd. National Communication on Climate Change, and to the authorities of the cemeteries for allowing our work at the sites. This study was supported by Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET PIP 112-201301-00038). AEC, MVC and DV are Researchers of CONICET.

References

Bar-Zeev, M., 1958. The effect of extreme temperatures on different stages of *Aedes aegypti* (L.). Bull. Entomol. Res. 48, 593–599.
Brady, O., Johansson, M., Guerra, C., Bhatt, S., Golding, N., Pigott, D., et al., 2013. Modelling adult *Aedes aegypti* and *Aedes albopictus* survival at different temperatures in laboratory and field settings. Parasit. Vectors 6, 351.
Camilioni, I., Barrucand, M., 2012. Temporal variability of the Buenos Aires, Argentina, urban heat island. Theor. Appl. Climatol. 107, 47–58.
Carbajo, A.E., Curto, S.I., Schweigmann, N.J., 2006. Spatial distribution pattern of oviposition in the mosquito *Aedes aegypti* in relation to urbanization in Buenos Aires: southern fringe bionomics of an introduced vector. Med. Vet. Entomol. 20, 209–218.
Cardo, M.V., Vezzani, D., Rubio, A., Carbajo, A.E., 2014. Integrating demographic and meteorological data in urban ecology: a case study of container-breeding mosquitoes in temperate Argentina. Area 46, 18–26.
Carrizo Páez, R., Carrizo Páez, M., Murúa, A., 2016. First record of *Aedes aegypti* (Diptera: culicidae) in San Juan, Argentina. Revista de la Sociedad Entomologica Argentina 75, 93–95.
Christophers, R., 1960. Aedes Aegypti (L.), the Yellow Fever Mosquito, 1st ed. Cambridge University Press, Cambridge.
Chuchuy, A., Rodriguero, M.S., Ferrari, W., Ciota, A.T., Kramer, L.D., Micieli, M.V., 2018. Biological characterization of *Aedes albopictus* (Diptera: culicidae) in Argentina: implications for arbovirus transmission. Sci. Rep. 8, 5041.
Couret, J., Benedict, M., 2014. A meta-analysis of the factors influencing development rate variation in *Aedes aegypti* (Diptera: culicidae). Ecology 14, 3.
CEDA, 2017. CRU TS3.24.01: Climatic Research Unit (CRU) Time-Series (TS) Version 3.24.01 of High Resolution Gridded Data of Month-by-month Variation in Climate (Jan. 1901- Dec. 2015). Centre for Environmental Data Analysis, University of East Anglia.
Curto, S., Bofia, R., Carbajo, A.E., Plastina, R., Schweigmann, N., 2002. Reinfestación del territorio argentino por *aedes aegypti*. Distribución geográfica (1994-1999). In: Salomón, O. (Ed.), Actualizaciones En Artropodología Sanitaria Argentina. Fundación Mundo Sano., Buenos Aires, pp. 302.
Díaz Nieto, L., Maciá, A., Perotti, M., Berón, C., 2013. Geographical limits of the southeastern distribution of *Aedes aegypti* (Diptera, Culicidae) in Argentina. PLoS Negl. Trop. Dis. 7, e1963.
Diez, F., Breser, V., Quirán, E., Rossi, G., 2014. Infestation levels and new records of*Aedes aegypti* (Diptera: Culicidae) in La Pampa Province, Argentina. Rev. Chil. Entomol. 39, 67–72.
Grech, M., Visintin, A., Laurito, M., Estallo, E., Lorenzo, P., Rocía, I., et al., 2012. New records of mosquito species (Diptera: Culicidae) from Neuquén and La Rioja provinces, Argentina. Revista Saude Publica 46, 387–389.
Gubler, D.J., 2011. Dengue, urbanization and globalization: the unholy trinity of the 21st century. Trop. Med. Health 39, 3–11.
Harris, I., Jones, P.D., Osborn, T.J., Lister, D.H., 2014. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. Int. J. Climatol. 34, 623–642.
Honorio, N.A., Silva, W., da, C., Leite, P.J., Goncalves, J.M., Lounibos, L.P., Lourenco-de-Oliveira, R., 2003. Dispersal of *Aedes aegypti* and *Aedes albopictus* (Diptera: Culicidae) in an urban endemic dengue area in the State of Rio de Janeiro, Brazil. Memorias Instituto Oswaldo Cruz 98, 191–198.
IGN - Instituto Geográfico Nacional, 2017. Cartographer Curvas De Nivel. Buenos Aires: Presidencia de la Nación.
INDEC – Instituto Nacional de Estadísticas y Censos (2017). (https://www.indec.gob.ar/bases-de-datos.asp?solapa=5). Accessed 10 June 2017.
Kraemer, M.U.G., Sinka, M.E., Duda, K.A., Mylne, A.Q.N., Shearer, F.M., Barker, C.M., et al., 2015. The global distribution of the arbovirus vectors *Aedes aegypti* and *Ae. Albopictus*. Elife 4, 1–18.
Li, C., Guo, X., Deng, Y., Xing, D., Sun, A., Liu, Q., et al., 2017. Vector competence and transovarial transmission of two *Aedes aegypti* strains to Zika virus. Emerg. Microbes Infect. 6, e23.
Lobo, J.M., Jiménez-Valverde, A., Real, R., 2008. AUC: a misleading measure of the performance of predictive distribution models. Glob. Ecol. Biogeogr. 17, 145–151.
Meinshausen, M., Smith, S., Calvin, K., Daniel, J., Kainuma, M., Lamarque, J.-F., et al., 2011. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. Climate Change 109, 213–241.
MSM - Ministerio de Salud de Mendoza, 2009. División Zoonosis RyV. Programa Dengue. 2009. .
O´Meara, G., Gettman, A.D., Evans, L.F.Jr., Scheel, F.D., 1992. Invasion of cemeteries in Florida by *Aedes albopictus*. J. Am. Mosq. Control Assoc. 8, 1–10.
R Core Team. R: A language and environment for statistical computing. (http://www.R-project.org/). Accessed 1 Mar 2016.
Rossi, G., Lestani, E., D'Oria, J., 2006. Nuevos registros y distribución de mosquitos de la Argentina (Diptera: culicidae). Revista Sociedad Entomologica Argentina 65, 51–56.
Rubio, A., Cardo, M.V., Vezzani, D., 2011. Tire-breeding mosquitoes of public health importance along an urbanization gradient in Buenos Aires, Argentina. Memorias Instituto Oswaldo Cruz 106, 678–684.
Rubio, A., Cardo, M., Carbajo, A.E., Vezzani, D., 2013. Imperviousness as a predictor for infestation levels of container-breeding mosquitoes in a focus of dengue and Saint Louis encephalitis in Argentina. Acta Trop. 128, 680–685.

SADS – Secretaria de Ambiente y Desarrollo Sustentable de la Nación, 2017. Cambio Climático En Argentina: tendencias Y Proyecciones. Tercera Comunicación Nacional sobre Cambio Climático Accessed 5 June 2017. http://3cn.cima.fcen.uba.ar/3cn_informe.php.

Silver, J.B., 2008. Mosquito ecology. Field Sampling Methods. Springer, Dordrecht.

Tsuda, Y., Suwonkerd, W., Chawprom, S., Prajakwong, S., Takagi, M., 2006. Different spatial distribution of *Aedes aegypti* and *Aedes albopictus* along an urban-rural gradient and the relating environmental factors examined in three villages in northern Thailand. J. Am. Mosq. Control Assoc. 22, 222–228.

Vezzani, D., 2007. Artificial container-breeding mosquitoes and cemeteries: a perfect match. Trop. Med. Int. Health 12, 299–313.

Vezzani, D., Carbajo, A.E., 2008. *Aedes aegypti*, *Aedes albopictus*, and dengue in Argentina: current knowledge and future directions. Memorias Instituto Oswaldo Cruz 103, 66–74.

Vezzani, D., Velazquez, S., Soto, S., Schweigmann, N., 2001. Environmental characteristics of the cemeteries of Buenos Aires City (Argentina) and infestation levels of *Aedes aegypti* (Diptera: Culicidae). Memorias Instituto Oswaldo Cruz 96, 467–471.

Visintín, A., Laurito, M., Diaz, L., Benitez Musicant, G., Cano, C., Ramírez, R., Almirón, W.A., 2009. New records of mosquito species for central and cuyo regions in Argentina. J. Am. Mosq. Control Assoc. 25, 208–209.

WHO – World Health Organization, 2018. Yellow Fever – Brazil. Accessed 25 January 2018. http://www.who.int/csr/don/22-january-2018-yellow-fever-brazil/en/.

Zanotti, G., De Majo, M., Alem, I., Schweigmann, N., Campos, R., Fischer, S., 2015. New records of *Aedes aegypti* at the southern limit of its distribution in Buenos Aires province, Argentina. J. Vector Ecol. 40, 408–411.

Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A., Smith, G.M., 2009. Mixed Effects Models and Extensions in Ecology With R. Springer, New York.